Synopsis

Ph.D in Computer Science

A Framework for Developing an Enhanced Convolutional Neural Network-Based Ensemble Learning Model for Alzheimer's Disease Classification Using MRI Brain Images

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1. INTRODUCTION

The futuristic technologies in health care segment are completely contradictory from any other industry. An innovation in image collecting devices leads to tremendously huge data collection that is demanding and exciting for image analysis. A widespread of efforts are needed by radiologists and medical practitioner to handle huge amount of image data. The practice of Artificial Intelligence (AI) techniques along with Machine Learning (ML) techniques and Deep Learning (DL) approaches can automate the diagnosis process which is complex and handle other issues related to the medical data. The evolution of AI in medical imaging has enhanced the clinical outcomes like speeding up the scan duration, creating accurate diagnoses and simplifying the medical imaging process. Medical experts interpret the medical image data which is complex and subjective by applying AI approaches. The present study focuses on the brain neuron images in classifying the stages of Alzheimer's Disease (AD), which aids the neurologists to understand the complex changes in the brain. The study aims to diagnosis AD at its early stages by analyzing the brain Magnetic Resonance (MR) images.

AD is a deteriorating brain ailment affected by the impairment of brain cells that causes memory loss and intellectual damage that affects millions of old age people across the globe. In 1906, AD was titled after Dr. Alois Alzheimer who observed few significant alterations in the brain nerves of a patient who had discomfort from psychological ailments like undergoing memory loss, communication difficulties, unfamiliar manners, etc. (Lane et al., 2018). When the patient expired, Dr. Alzheimer examined the patient's brain and recognized numerous abnormalities. AD is a permanent brain ailment that steadily wear away thinking and memory skills which finally disturbs even the basic tasks (Sengoku 2020). Neuroimaging method aids to measure the abnormal changes in the brain images by examining the stand-in markers. Hence, a technique to measure the abnormal changes in the brain is required. An effective neuroimaging tools like Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single Photon Emission Computerized Tomography (SPECT) aids in finding changes in the brain due to neurodegenerative ailments. These diverse

imaging techniques aids in envisioning the functional structures and detecting precise changes and anomalies in the brain. Compared to other neuroimaging tools MRI is better and widely used for AD analysis (Arora et al., 2022).

Fuadah et al., (2021, March) designed an automated AD classifier using a CNN model with AlexNet architecture. The SVM classifier is used to perform classification in this study. A DL algorithm is used in the development of multilayer perceptron for 2D structure image. Every layer in the CNN model aids to identify the selection of images. Image processing techniques are applied to develop images with different resolutions. The output of each image is given as the input of the next layer. The CNN architecture aids in feature extraction and classification. Convolutional operation, Rectified Linear Unit (ReLU) and pooling are the operation performed for feature extraction. Fully connected, and activation function operations are performed for classification. A predictive system for AD development is vital which is based on the symbols and symptoms is required. The automated AD classification model should assists the medical personnel to diagnose the stage of AD which aids to provide appropriate medical treatment.

Kumar et al., (2022) came up with an AlexNet framework for classifying MR images to diagnosis AD at the Mild Cognitive Impairment (MCI) stage. The key objective of the framework is the transfer learning technique to discriminate MCI and the elementary controls involved in the Alexnet framework. The brain MR images are separated as axial, sagittal, and frontal to evaluate and classify the components. It is vital to inspect the group of artifacts discovered by vectors instead of each pixel separately in order to study the images. All the images are examined by the CNN model to identify permanent features from the MR images. The convolutional layers allows hierarchical identification of features which is a challenging task in MR images. The proposed framework is evaluated only using OASIS dataset.

Oktavian et al., (2022) developed a CNN model with ResNet-18 architecture to solve image recognition issues. DL is applied due to its strong learning abilities to handle challenges related to huge datasets, the need for huge computing resources and the

demanding parameter setting to avoid over fitting or under fitting. Transfer learning is applied along with the weighted loss function to assign same weights to each class. The ReLU activation function is replaced by the Mish activation function to enhance the accuracy. The proposed model used transfer learning, weighted loss and the Mish activation function which does not demonstrate a major surge in the accuracy attained.

Salehi et al., (2020, September) proposed a CNN model for primary diagnosis and classification of AD using MR images. The CNN layer consists of convolution, ReLU, pooling, dropout, fully connected layers. The initial convolution layer takes the input image and it recognizes the association between the image and its features. The next layer is the ReLU activation layer used to enhance the non-linear properties in the CNN model. The final layer enhances the model's training performance and is given as input to the fully connected layer. The use of deep CNN to deal with huge volume of data can improve the algorithm in early detection of AD. Das et al., (2021, November) came up with an AD prediction model to extract features like homogeneity, correlation and contrast. Random forest classifier aids to classify the size and the shape of the vital parts of the brain.

To link the gap amid these techniques, this study proposes novel techniques in AD classification using CNN models to handle the above-mentioned concerns. The research problem is expressed as follows.

The main aim is to apply Deep Learning (DL) algorithms for identifying and predicting the AD and classify patients with AD based on the different stages. A forecast and identification tool is proposed which aids the radiologists, medical professionals, caregivers to reduce time, cost and aids patients suffering from AD. The use of DL algorithms aids in the diagnosis of AD which performs better with large datasets. Advanced medical imaging practices, particularly in the brain neuron images, support the neurologist in choosing suitable treatment plan, discovering anomalies present in the human brain. Innovative and computationally progressive methods for brain neuron image analysis are required to create qualitative valuations in AD classification. The identification of AD from brain neuron images involves a computerized system to categorize the neuron images. Hence, an

automated system to categorize AD at an early stage through organized screening procedure is mandatory to provide a more accurate diagnosis.

To handle the research problem, the primary objectives of this research is given below.

Primary Objective: To enhance the classification performance of Alzheimer Disease detection using enhanced Machine Learning and Deep Learning hybrid techniques based on ensemble classification framework

Additionally, to address the primary objectives, the secondary objectives are created and are given below.

Secondary Objectives:

- To enhance brain neuron MRIs by removing noise and artifacts using denoising techniques, leading to improved classification performance.
- To improve classification performance in Alzheimer Disease detection by developing a segmentation technique that accurately extracts the middle slice of the brain while preserving fine details.
- To enhance the classification process using feature extraction with CNN-based method and conventional techniques.
- To predict and classify the various stages of Alzheimer's Disease using ensemble classification algorithms for improving the classification performance.

2. RESEARCH METHODOLOGY

To process huge amount of data using CNN models, there is a need for a vital amount of resources. The system configuration details, and the dataset description are given below. The experiments are performed using Intel Core i7 7th generation processor, 2.7 GHz, 8 GB RAM, 2TB SSD, and Windows 10 operating system. The proposed method is evaluated using Matlab 2020b tool. The Graphics Processing Unit (GPU) used is NVIDIA GeForce RTX 2080. In this study, MR images from two different standard datasets like ADNI and OASIS were used.

Primarily, the process begins with image data acquisition. Pre-processing is achieved in two stages: 1. De-noising 2. Segmentation. During image de-noising, various techniques, like wiener filter, weighted median filter, adaptive filter, hampel filter, and Adaptive Hampel Identifier Filter (AHIF) method (proposed technique), are applied. The objective of executing pre-processing is to exclude Gaussian and salt & pepper noises and highlight AD features for better diagnosis. Removal of noise from the image is performed without any loss of features such as spatial and edges. The preprocessing task develops the image contrast by applying histogram-based image enhancement. These methods enhance the image quality and aids as a vital foundation for consequent classification tasks.

Segmentation is performed by applying adaptive noise filtering techniques to the neuron image. Here, image segmentation is performed for effective skull stripping operation by applying techniques like region growing technique, histogram-based thresholding in Discrete Wavelet Transform (DWT) and Fuzzy c-means clustering are performed. The proposed hybrid segmentation technique named Threshold DWT based using Fuzzy Set Theory (TDWT-FST) performs fuzzy edge detection and morphological operations are applied.

Feature extraction is carried out using conventional methods and a transfer learning method to overcome the imbalance issues. A pre-trained AlexNet model is used for feature extraction, by transferring the initial layer from this model and the features are extracted from CNN. This process aids to identify AD at an early stage.

Classification is carried out from the extracted features using ML algorithms such as DT, KNN, SVM, NEAT, and BAGGING for AD stage classification. In this study, two hybrid classification techniques are proposed such as a hybrid classification technique that combines BAGGING and NEAT approaches and another hybrid classification technique that combines BAGGING and SVM approaches to classify brain neuron images.

2.1 Preprocessing and segmentation

MR image De-noising is the prime research point in the area of image processing. During the image capturing, processing and storing process, the quality of the image gets defective. Hence, removing and reducing the noise from the original MR image is a vital process. However, while removing the noise, artifacts are introduced and image blurring occurs to the MR image which is an inspiring issue for researchers. The denoise filtering methods describes the spatial domain methods, transformed domain methods and manipulating statistical properties signals. The filtering in spatial domain gears an average of pixels in minimizing the noise (Ali 2018). The filtering techniques can be generally characterized as spatial domain and frequency domain. The linear and non-linear filtering procedures, a wavelet-based denoising procedure and segmentation are discussed in detail.

The brain images of the AD patient is used to effectively de-noise the MRI images. The initial contribution of the proposed method is effective handle various levels of the Gaussian noise present in the grayscale images. Removal of noise from the image is performed without any loss of features such as spatial and edges. The smoothening effect is produced in the Gaussian filter. The smoothening ratio depends on the Gaussian function given in equation (1).

$$G_{\sigma}(i, j) = \frac{1}{2\Pi\sigma^2} e^{-\frac{(i^2+j^2)}{2\sigma^2}} \quad (1)$$

Here ‘i’ and ‘j’ denotes the vertical and horizontal axis from the centre σ denotes the distribution of standard deviation.

In this work, an Adaptive Hampel Identifier (AHI) noise removal technique is proposed for effective noise as well as artifacts elimination. The HI is a traditional one, only deliberate forwards then backwards image data of present position, while the observation is 2D. In image processing system, it’s obviously derive up with the idea, which use the identify window from 1D to 2D. The pseudo code of the proposed hybrid method is presented.

Input: Noisy image $Y \in R^{M*N}$

For each pixel $x_m(n)\, in\, Y\, do$

Calculate median $\mu_m(n)$ and median absolute deviation $\sigma_m(n)$,

$$\mu_m(n) = med\{F_w(x_m(n))\},$$
$$\sigma_m(n) = 1.4826.med\{A(|\, x_m(n)\,|)\}$$

Where $x_m(n)$ is the element located at m^{th} row and n^{th} column of X, 2W+1denotes the length of sample windows.

Calculate the adaptive rejection threshold

$$\Gamma = \frac{c}{win_{\max} - win_{\min} + \in_1}$$

Where c=256 for grey scale images, $\in_1 >0$ is a small positive constant and win_{max} and win_{min} denote the minimum and maximum detect window

$$win_{\max} = \max Fw(x_m(n))$$
$$win_{\min} = \min Fw(x_m(n))$$

End

2.2 Feature extraction

The feature extraction is performed using conventional Gray-Level Co-occurrence Matrix (GLCM), Gray-Level Run Length Matrix (GLRM) and Gray-Level Dependence Matrix (GLDM) method along with the proposed CNN based pre-trained AlexNet.

2.2.1 Conventional GLCM, GLRM and GLDM

GLCM technique computes statistical characteristics based on the spatial connection between the intensities of individual pixels in the image. The results of these calculations provide information about the patterns and structures of texture. The GLRM technique pulls out run length features, which keep track of how long sequences of pixels with the same

intensity value. The GLDM extracts the run length features, which capture the lengths of consecutive pixels with the same intensity value. These features provide insights into the continuity of the texture.

2.2.2 AlexNet

In this study, a pre-trained CNN deep learning model AlexNet is applied to extract the features automatically for classifying AD using MR images. The performance of a CNN model are evaluated using different metric measures. The extracted features are given as input to the classifier model to classify the brain image as normal and abnormal images within the AD stages. A CNN model is built for feature extraction which aids to extract features automatically by analysing the extracted features from the fully connected layer. The AlexNet contains 5 convolution layers, 3 max-pooling layers, 2 Normalized layers, 2 fully connected layers and 1 SoftMax layer. There is a convolution filter and a non-linear activation function named as “ReLU” in each convolution layer. The pooling layers performs the max-pooling function and the input size is static due to the occurrence of fully connected layers. The input size is 224x224x3 in most places due to padding that occurs to be 227x227x3. Over all the AlexNet has over 60 million parameters (Nawaz et al., 2021).

2.3 Classification

In this study, the most well-known conventional ML classifiers are hybridized and applied (BAGGING_SVM, and BAGGING_NEAT) for each set of features and for evaluating the results. To build an automated AD diagnosis method, a pre-trained CNN based AlexNet are applied to extract features from the brain MR image. Then two different hybrid classifiers BAGGING_SVM, and BAGGING_NEAT are proposed. Finally, the different results obtained are analyzed efficiency for each method using evaluation metrics, and the results are compared with recent studies.

2.3.1 BAGGING_ SVM

In this study, the ensemble of Bootstrap Aggregating (BAGGING) and Support Vector Machine (SVM) are applied to enhance the classification accuracy, avoid overfitting and reinforce the constancy of the proposed method. BAGGING process which trains SVM models on several subsets of trained data and combining their predications to enhance the

complete performance. The BAGGING_SVM classification method minimizes the variance and simplification error by aggregating predictions from several SVM models trained on discrete data subsets which results in an enhanced classification accuracy. The pseudo code of the BAGGING_SVM classification method is give below.

Ensemble Bagging_SVM

Select:

X: Features of training data

y: Labels or targets for training data in classification (for regression)

B: Bootstrap sample count - SVM parameters (e.g., regularization parameter C, kernel type)

SVM_models = [] to initialize the ensemble of SVM models.

Regarding b = 1 to B:

Step 1: Samples using bootstrap

Establish a bootstrap example: bootstrap_sample(X, y) = X_b, y_b

Step 2: Train an SVM model in step two.

Train an SVM model on X_b and Y_b with provided parameters.

SVM_model_b = Train_SVM(SVM_parameters, X_b, y_b)

#Step 3: Keep the ensemble's trained SVM model stored.

Add SVM_model_b to the SVM_models list.

Step 4: Aggregating Predictions (majority voting for categorization, averaging for regression)

For every new instance of x_new:

assemble all SVM_models' predictions for x_new

if Classification: By majority vote, aggregate projections

majority_vote(predictions) = predicted_label Store Expected_label

If Regression is used, average the predictions to create an aggregate.

Predicted_value = average(predictions)

Store Predicted_value

2.3.2 BAGGING_NEAT

In this study, the ensemble of BAGGING and Neuro Evolution of Augmenting Topologies (NEAT) are applied to enhance the classification accuracy and simultaneously encourage diverse viewpoints and individual precision. The pseudo code of the BAGGING_NEAT classification method is give below.

Data Preparation:
Input: Data (X) and Labels (Y)
NEAT Evolution:
Initialize NEAT parameters and population
Repeat until convergence criteria are met:
Generate new neural network topologies using NEAT
Evaluate the fitness of each network using the provided dataset.
Select parents and perform genetic operations (mutation, crossover) to create offspring
Replace the population with the offspring
Bootstrap Sampling:
Input: NEAT-evolved networks (NEAT_networks)
For each bootstrap iteration:
Create a bootstrap sample by randomly selecting data points with replacement
For each NEAT network in NEAT_networks:
Train the network on the bootstrap sample
Prediction and Aggregation:
Input: Test data (X_test)
For each NEAT network in NEAT_networks:
Obtain predictions for X_test using the trained network
Ensemble Combination:
Apply an aggregation technique (e.g., majority voting or averaging) to combine the predictions of NEAT networks
Evaluation and Performance Analysis:
Input: Combined predictions and accurate labels for test data (ensemble_predictions, Y_test)
Calculate evaluation measures using ensemble_predictions and Y_test
Output: Evaluation results

3. RESULTS AND DISCUSSION

The study uses ADNI and OASIS benchmark datasets. The Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are the three-performance measures used in this study to assess the proposed hybrid AHIF method. Tables 1 and 2 illustrates the performance metrics of preprocessing techniques on the ADNI and OASIS datasets.

Table 1. Performance Metrics of Preprocessing Techniques on ADNI dataset

Performance Metric	Preprocessing Techniques on ADNI Dataset				
	Wiener Filter	Weighted median Filter	Adaptive Filter	Hampel Filter	Proposed AHIF
PSNR	20.46	22.5	23.68	25.88	30.05
SSIM	0.39	0.48	0.64	0.85	0.95
RMSE	0.68	0.39	0.64	0.55	0.23

Table 2. Performance Metrics of Preprocessing Techniques on OASIS dataset

Performance Metric	Preprocessing Techniques on OASIS Dataset				
	Wiener Filter	Weighted median Filter	Adaptive Filter	Hampel Filter	Proposed AHIF
PSNR	22.58	26.08	27.64	26.7	29.88
SSIM	0.43	0.5	0.67	0.83	0.9
RMSE	0.7	0.43	0.52	0.63	0.3

The RMSE values of ADNI dataset 0.23 and OASIS dataset is 0.3. The proposed AHIF hybrid method outperforms the other techniques on ADNI and OASIS datasets. The PSNR values obtained by the proposed AHIF method on ADNI and OASIS datasets are 30.05 decibel and 29.88 decibel, respectively. The AHIF hybrid method overhauls the other methods on ADNI and OASIS by obtaining the maximum PSNR value equated to the other methods. The SSIM values obtained by the proposed AHIF hybrid method on ADNI and OASIS datasets are 0.95 and 0.9, respectively. The AHIF hybrid method outperforms the other methods on ADNI and OASIS by obtaining the maximum SSIM value equated to the other methods.

Tables 3 and 4 illustrates the performance metrics of segmentation techniques on the ADNI and OASIS datasets.

Table 3. Performance Metrics of Segmentation Techniques on ADNI dataset

Performance Metrics	**Segmentation Techniques on ADNI Dataset**		
	Region Growing	**Histogram Based Thresholding**	**Proposed TDWT-FST**
RMSE	0.44	0.75	0.38
PSNR	52.69	53.19	56.28
MAE	1.04	0.57	0.36

Table 4. Performance Metrics of Segmentation Techniques on OASIS dataset

Performance Metrics	**Segmentation Techniques on OASIS Dataset**		
	Region Growing	**Histogram Based Thresholding**	**Proposed TDWT-FST**
RMSE	0.62	0.88	0.42
PSNR	54.68	57.35	58.03
MAE	1.02	0.61	0.35

The RMSE values of ADNI dataset 0.38 and OASIS dataset is 0.42. The proposed TDWT-FST method outperforms the other techniques on ADNI and OASIS datasets. The PSNR values obtained by the proposed TDWT-FST method on ADNI and OASIS datasets are 56.28 decibel and 58.03 decibel, respectively. The TDWT-FST method overtakes the other methods on ADNI and OASIS by obtaining the maximum PSNR value equated to the other methods. The MAE values of ADNI dataset 0.36 and OASIS dataset is 0.35. The proposed TDWT-FST method outperforms the other techniques on ADNI and OASIS datasets.

Tables 5 and 6 illustrates the performance comparison of AlexNet with BAGGING_SVM and AlexNet with BAGGING_NEAT techniques on the ADNI and OASIS datasets. The AlexNet with BAGGING_SVM method on the ADNI dataset achieved 91.6% accuracy, 94.9% precision, 91.2% recall, and 90.5% F1-Score. The AlexNet with BAGGING_SVM method on the OASIS dataset has obtained 89.2% accuracy, 82.7% precision, 85.7% recall, and 81.8% F1-Score. The performance of the ADNI dataset exceeds the performance of the OASIS dataset.

The AlexNet with BAGGING_ NEAT method on the ADNI dataset achieved 97.5% accuracy, 96.9% precision, 99.2% specificity, 94.1% recall, and 97.8% F1-Score. The AlexNet with BAGGING_ NEAT method on the OASIS dataset has obtained 95.8% accuracy, 94.9% precision, 97.6% specificity, 98.4% recall, and 94.6% F1-Score. The performance of the ADNI dataset exceeds the performance of the OASIS dataset.

Table 5 Performance comparison of AlexNet with BAGGING_SVM on ADNI and OASIS dataset

Datasets	Classification Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ADNI	AlexNet + BAGGING_SVM	**91.6**	**94.9**	**91.2**	**90.5**
OASIS	AlexNet + BAGGING_SVM	**89.2**	**82.7**	**85.7**	**81.8**

Table 6 Performance comparison of AlexNet with BAGGING_NEAT on ADNI and OASIS dataset

Datasets	Classification Method	Accuracy (%)	Precision (%)	Specificity (%)	Recall (%)	F1-Score
ADNI	AlexNet +	**97.5**	**96.9**	**99.2**	**94.1**	**97.8**
OASIS	AlexNet +	**95.8**	**94.9**	**97.6**	**98.4**	**94.6**

4. CONCLUSION

This study aimed to enhance the AD classification performance which aids the medical experts to interpret the medical image data and discovering neurological ailments like AD using computational techniques. Globally every year there is an increase in the number of patients affected with dementia. AD is the key cause of dementia in older adults and is currently the next foremost reason of death worldwide. Cognitive functioning issues in older adults are affected by AD. The person's ability is affected which is a challenging to perform the daily routine tasks. There is a lack of awareness related to cognitive damage and dementia precaution. AD can cause destructive impact on social and economic status. If AD is diagnosed at an early stage, it can lead to a good life with sound mental health. This research emphasis on early detection and classification of AD in older adults which aids to increase the patient maintenance and their life time.

In this study, MR images from two different standard datasets like ADNI and OASIS were used. The pre-processing is achieved in two stages such as de-noising and segmentation. During image de-noising, various techniques, like wiener filter, weighted median filter, adaptive filter, hampel filter, and the proposed AHIF method are applied. Segmentation is performed by applying adaptive noise filtering techniques to the neuron image. Image segmentation is performed for effective skull stripping operation by applying techniques like region growing technique, histogram based thresholding in DWT and Fuzzy c-means clustering are performed. The proposed hybrid segmentation TDWT-FST technique performs fuzzy edge detection and morphological operations are applied. For feature

extraction, a pre-trained CNN deep learning model AlexNet is applied to extract the features automatically for classifying AD using MR images. The performance of a CNN model are evaluated using different metric measures. The extracted features are given as input to the classifier model to classify the brain image as normal and abnormal images within the AD stages. The two different hybrid classifiers such as BAGGING_SVM, and BAGGING_NEAT are proposed. Finally, the different results obtained are analyzed efficiency for each method using evaluation metrics, and the results are compared with recent studies. The performances of all the proposed methods were assessed and compared using the considered metrics. The proposed AlexNet with BAGGING_NEAT method is found to be optimal on ADNI and OASIS dataset. Hence, this research is concluded productively by achieving all the objectives with an aim to enhance the classification performance.

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